Clean Your Hands: Using Computational Modeling to Improve Infection Rates in Anesthesia Induction*

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Abstract— **In United States healthcare, there are persistent problems associated with infections, especially in relation to hand hygiene in anesthesia. While the sterile field of an operating room is well defined, cross contamination can still occur due to the complexity of the anesthesia work environment. This study aims to address this deficiency using a novel computational technique. Formal methods will be used to verify the cleanliness and properties associated with the anesthesia induction process as they dynamically evolve. Our hypothesis is that formal verification will be able to predict and identify how infection can spread in the operating room during the anesthesia induction process. This paper describes preliminary work demonstrating the feasibility of the modeling underlying this approach.**

Despite the significant international emphasis on hand hygiene and infection control in healthcare, the United States has failed to meaningfully reduce infection rates [1]. Hand hygiene in the perioperative environment is well defined for sterile areas. However, there is a lack of such clarity within the anesthesia work environment [2]. As a result, hand hygiene issues are a major contributor to healthcare-associated infections (HAIs): infections contracted within 48 hours of hospital admission, three days of discharge, or 30 days of an operation. HAIs can be associated with significant morbidity and mortality as well as lead to sepsis, which accounts for over 250,000 deaths annually in the United States [3], [4].

This is a complex problem because it involves multiple people operating concurrently, while potentially touching many difference pieces of equipment. This can allow potential infections to spread around the operating room (or even between procedures) due to unforeseen interactions between the patient, medical professionals, each of the medical professionals' different hands, and equipment. This also makes it difficult to predict how changes in procedures or the introduction of interventions could affect hygiene. Furthermore, the speed with which anesthesia induction tasks must be performed and the high stakes/stress of the work can result in erroneous behaviors where important hygiene steps are omitted [5].

This study seeks to address this problem using a novel computational technique. In particular, the computer science field of formal methods has developed tools and techniques for formally verifying (mathematically proving) whether models exhibit desirable properties (i.e., specifications). Model checkers are tools for automatically performing these verifications, and variants can even compute the probability of specifications holding [6], [7]. Previous work has explored how model checking and human reliability concepts can be used to find failures in healthcare systems [8], [9], [10], [11], [12]. It is our hypothesis that model checking will allow us to identify and predict how infections can spread around an OR in ways that could compromise patient health. We are developing a new method that will enable the following:

1) identification of deficiencies in normative procedures that could cause infection to be spread between patients;
2) identification of problems where unexpected erroneous human behavior can cause the spread of infection; and
3) exploration of interventions to reduce infection spread.

We envision our method taking the form shown in Fig. 1. First, the anesthesia induction process is observed. This involves an analyst tracking each step in the induction, initial cleanliness state of each object, movements of the operators (what each hand of the operator touches), and what objects interact with the patient and the environment. The observations are recorded in a spreadsheet that organizes the observations by step in the induction. Logical operators can be specified in the spreadsheet to indicate when there is nondeterminism (choice) in which person performs a step and/or which hands are used.

The spreadsheet is read by an automated translation program (currently implemented in Python). This converts the information in the spreadsheet into a computational formal model. In our current version of the method, the formal model is rendered in the PRISM language, the modeling formalism of the PRISM model checker [7]. The formal model contains two sub-models (or modules). The first simply tracks the steps in the procedure from the spreadsheet and ensures that the procedure executes. The second keeps track of the state of all objects in the environment (including each healthcare professional's hands). This includes the gloved state of healthcare workers' hands, the cleanliness or dirtiness of all objects (including hands and layers of gloves), and if/how dirtiness spreads. That is, a clean thing (including hands or gloves) becomes dirty if it touches something that is dirty. Gloved or ungloved hands that are dirty can become clean if a step specifies hand cleansing. Nondeterminism defined in the spreadsheet manifests as different optional transitions in the module.

The analyst must also describe specification properties they wish to check against the formal model. The PRISM model checker supports a number of different specification languages.

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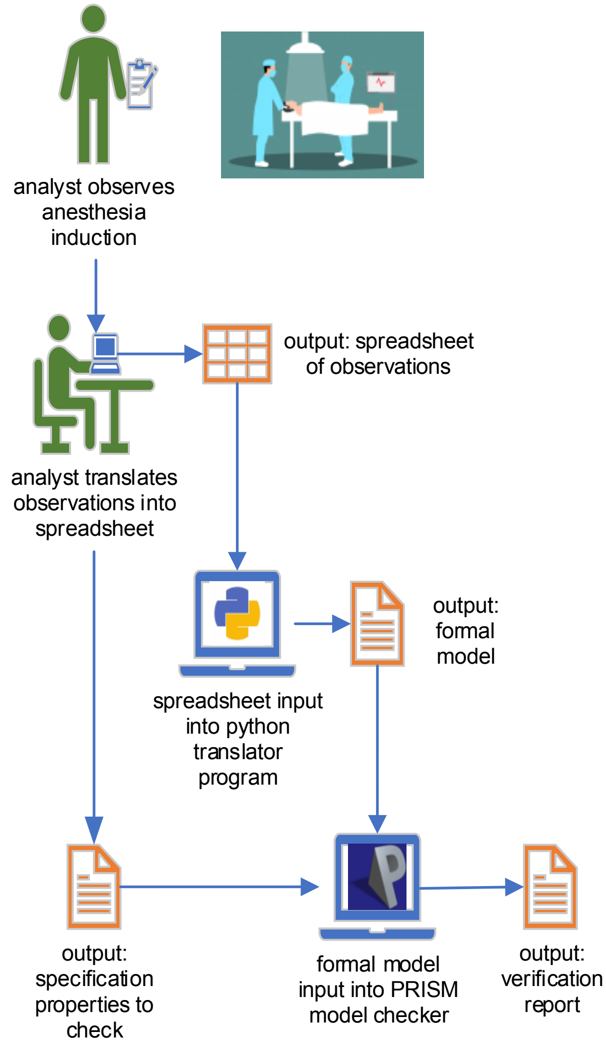

Fig. 1. Illustration of the computational modeling approach for analyzing an anesthesiology induction procedure. The green analyst observes the induction procedure. The analyst documents the observations in a spreadsheet. The spreadsheet is input into the python translator that outputs the formal model. The formal model is input to the PRISM model checker which outputs a verification report. This is either a confirmation or a counterexample, which illustrates how a specification property was violated.

The current implementation does not contain any probabilistic information, thus we are currently testing symbolic model checking (that is, checking properties that do not contain stochastic information). As such, most of the specifications we have defined are safety properties of the form:

$$\textbf{AG}\ \neg(BadThing)\,. \tag{1}$$

That is, we are asserting that, through all paths through the model ($\textbf{A}$), it should always/globally be true ($\textbf{G}$) that a bad thing never happens ($\neg(BadThing)$). For example, the IV should never be dirty. This is specified as:

$$\textbf{AG}\ \neg(IV = Dirty)\,. \tag{2}$$

Our current work is focused on checking the full induction procedure. We modeled our current procedure on publicly available information. We are analyzing it to confirm that, within the model's normative procedures, there is nothing that becomes incorrectly dirty. Future work will extend our methods to account for the procedural variations and nondeterminism that is specific to the University of Virginia (UVA) Health Systems's induction process. Additional future work will look to model human reliability and the stochasticity of other events that can interrupt the procedural flows of induction. Finally, we plan to investigate how different interventions will impact outcomes in the hopes of creating robust procedures. For example, UVA Health Systems has been testing place mats which designate dirty and clean spaces for objects. Our model should be able to investigate the effectiveness of this effort and explore other options that could reduce HAIs. We hope this flexible tool will be available to any hospital to enable them to evaluate their induction procedures and assess the effectiveness of interventions.

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